Discovering Hidden Emotional Heterogeneity of Customers in Textual Reviews and its Influencing Factors

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Abstract

E-commerce platforms are recognizing the value of customer experience and are dedicating sections for customers to share reviews of the product purchased. Therefore, this study aimed to analyze Online Customer Review (OCR) to identify hidden emotion expressed about the purchasing experience and further identify factors relating to the product. Text-based emotion classification is a prominent and growing field to better understand human emotions. An integrated Information Gain-Recursive Feature Elimination (IG-RFE) and stacking ensemble learning were implemented to develop a predictive emotion classification model to identify the hidden emotions of the customers. Additionally, the Latent Dirichlet Allocation (LDA) model was used to extract the influencing factors, providing further insight in OCR. The study extracted eight emotions from OCR and seven influencing factors from product's attributes. The emotions included anger, anticipation, disgust, fear, happiness, sadness, surprise, and trust while the identified factors were quality, brand credibility, product functionality, usability, appearance, price, and functional effect. The extracted emotions and factors from the OCR provided valuable knowledge on the study. The findings showed knowledge gaps in emotion classification and customer behavior fields, suggesting further investigation for future study.

Keywords: customer behavior, emotion classification, ensemble learning, feature selection, online customer review, topic modelling.

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1. Introduction

Expressions are communicated through individuals in multidimensional methods. Despite the variety of emotions represented by expressions, human affections are difficult for both computers and humans to understand. Furthermore, individuals may reflect the same emotion in different ways or show multiple affections simultaneously, which contributes to the cause of the problem [1]. This complexity shows the challenges of emotion analysis, as it includes determining the emotional state of a person through a variety of expressions. In addition, various data sources are used for the analytical processes, including text, images, audio, and video [2-5]. Writing is the primary channel for individuals to communicate thoughts and feelings, specifically with the growth of social media where various feelings and sentiments are expressed [6].

Many customers post reviews regarding various products and services on different e-commerce websites. E-commerce platform provides review sections to express the views and experiences of customers about products [7]. Before making a purchase, different customers read at least seven reviews from previous users [8]. These reviews are considered valuable data that helps businesses understand the factors influencing customer satisfaction and improve products to meet future needs. Therefore, companies and potential customers should identify and extract the most important and useful information from reviews. This growth has led to the study of texts from social media platforms as well as the provision of various methods to determine sentiments and emotions [9-14]. Emotions as well as feelings are often misinterpreted and sentiment can be broadly divided into two categories, namely positive and negative, while emotion includes more specific feelings such as anger, anticipation, disgust, fear, happiness, sadness, surprise, and trust.

Sentiment develops gradually when an individual has a state of mind towards an object due to continuous thoughts or perceptions of the product, such as good or bad, positive or negative, etc. Aside from sentiment, emotions are based on more sophisticated and complex systems. Although the first method uses simplified binary categorization, the second method is based on a deeper analysis of human emotions and sensitivities. Some reasons why emotions are more important than sentiment include (1) Sentiment analysis oversimplifies the data, making a big mistake by reducing the complex limit of human emotions to simply positive and negative. When the exploration aims to leverage marketing strategies, dividing feedback into positive and negative will only lead to a superficial understanding of the customer. This implies that a deeper understanding of customer motivation is required. (2) Emotion provides more valuable insight different from sentiment. To understand the reason customers, ignore or do not read reviews, they need more than a negative or positive percentage but an accurate number that shows how a product is enjoyable, frustrating, or boring. (3) Emotion gives actionable insights, when a business knows exactly what emotions customers feel, it will be easier to act. Knowing what inspires a product makes it easier to understand where the product succeeds as well as fails and respond accordingly. However, classifying and analyzing emotion using OCR data requires time and resources.

In addition to recognizing emotions in each OCR, it is important to consider alternative perspectives to model and understand how customers evaluate the whole product. A proposal was made by Bassig [15] that text reviews in natural language offer more detailed information compared to numerical ratings, even though both types of reviews are customer feedback. The numerical rating of general performance, usually between 1 and 5, serves as a general sign of total customer satisfaction due to the ability to provide a comprehensive evaluation [16-17]. Due to the lack of information that customers could use, numerical evaluations of individual opinions are more biased and inadequate compared to text reviews [18]. Ganu *et al.* [16] also reported that text reviews more accurately reflect opinions compared to numerical ratings of predefined attributes on customer review platforms. Therefore, extracting attributes from review text is essential to understanding the opinion of customers about each feature of a product. To extract attributes from the review text, a topic modeling study based on Natural Language Processing (NLP) is required. Topic modeling is a statistical tool for uncovering topics/attributes from a series of text data. Subsequently, these attributes are used as factors that influence various emotions in OCR.

Previous studies have extracted emotions in OCRs, but there has not been any theoretical study on emotion and its influencing factors, nor have the factors that influence different emotions been identified. For instance, explorations conducted by Felbermayr & Nanopoulos [19], as well as Ren & Hong [20], extracted emotions in OCRs, and both studies also examined the relationship between emotions and the usefulness of the review. Review helpfulness was determined by the number of likes for each review received. Felbermayr & Nanopoulos [19] discovered that trust, joy, and anticipation were the most important emotions related to helpfulness. Following this, Ren & Hong [20] identified anger, fear, as well as sadness as major emotions and concluded that as sadness in review increases, perceived helpfulness decreases making both studies agree that emotions affect the usefulness of reviews.

In comparison to Felbermayr & Nanopoulos [19] and Ren & Hong [20], who identified emotions and analyzed how review helpfulness was affected, Dhar & Bose [21] discovered emotions and examined how they related to numerical rating. The study showed that among other recorded emotions, fear, happiness, and surprise influenced numerical ratings more than other emotions embedded in the review text. Another exploration by Ullah *et al.* [22] showed how two types of emotions were identified, namely positive and negative emotions. In addition, the study explored the distribution of emotions in OCR without observing the emotions related to a factor, different from previous studies.

Previous exploration lacked attention to product attributes that were hidden in OCRs but were often discussed by customers. Existing studies only extracted emotions in OCRs and examined the relationship between emotion and predetermined attributes provided on the platform. However, pre-defined attributes on the platform sometimes do not accurately reflect the opinions of customers because predetermined attributes cannot capture changes in the thoughts of buyers about the product. There is a need to discover emotions and identify attributes of the product that customers often discuss to explore the relationship between qualities of the product as influencing factors and emotions that impact customer purchasing decisions. Moreover, the study aims to identify hidden emotional heterogeneity and its influencing factors to generate total customer satisfaction in OCRs for currently available electronic products. Previous studies showed that customers make decisions based on personal preferences and the selection as well as consideration of various features of products [23]. Prior explorations also showed the trade-offs that customers make between different attributes, such as quality and price qualities [24]. When faced with real-world problems, customers need to make decisions that are much more complex than simply selecting between two or three different properties. The importance of purchasing decisions for diverse products varies greatly, even for the same attribute [25]. Therefore, it is crucial to have a deeper understanding of the attributes of the product that customers find most valuable, as various attributes have a significant impact on customer satisfaction [26]. A study by Gong *et al.* [25] proposed that certain characteristics of a product can trigger analysis of the benefit of customers and encourage buyers to develop positive purchasing preferences. However, the emotions of customers regarding different product characteristics are not always fixed, rather, the value varies depending on further product development [27]. The study is guided by the following three study questions because of the proposal in this manner.

RQ1. What is the hidden emotional heterogeneity identified in OCRs?

RQ2. What attributes of the products extracted in OCRs are considered to be influencing factors? Which attributes do customers consider to be more important and focused on?

RQ3. What are the overall evaluations of the products by customers? How is emotion expressed in OCRs related to identifiable products' attributes?

This study addressed a previously unexplored area in the integration of emotion classification and topic modelling. Specifically, we utilized Information Gain-Recursive Feature Elimination (IG-RFE) as two-stage feature selection to measure the feature importance, and stacking ensemble learning that combine multiple machine learning algorithms via meta learning to classify emotions. Last, we identified the most frequently discussed topics using Latent Dirichlet Allocation (LDA) topic modelling.

The significance of this study was, (1) Four electronic products were selected from an e-commerce platform creating a successful balance between various electronic products and also contributing to a more comprehensive expression of public opinion and preferences on currently available electronic products. Additionally, it helped marketers understand the attributes that the customers value and how those qualities influence the emotions of the buyers toward the product. (2) The result performed a large-scale data-driven exploration of the time, space, and emotional content of public consumption by using web crawler technology to gather online review data generated by users of e-commerce platforms, which was more authentic and comprehensive [28-30]. In addition to improving the ability to recognize changes in public opinion towards certain products, this could also improve the methods and data sources used in emotion classification studies [31].

2. Material and Methodology

2.1 Research Design

A comprehensive understanding of customer responses towards products was crucial for achieving deeper insights into the emotions. This study developed the various research designs namely (1) two-stage feature selection, which was used to obtain significant features for emotion classification on the OCR, (2) emotion classification, to determine the degree of feelings to various products' attributes, and (3) topic modelling, the factors or product's attribute from OCR were extracted using Latent Dirichlet Allocation (LDA). Subsequently, the attributes influencing the customers' emotions toward each product were further examined. The overall proposed model of this study is shown in **Fig. 1**.

2.2 Data Sources and Collection

The study selected OCR of four electrical products from a well-known e-commerce website called Amazon (amazon.com). The company was known for selling home appliances, electronics, clothes, as well as other items and operated in various countries, including the United States, Canada, Mexico, Brazil, the United Kingdom, Germany, France, Italy, Spain, the Netherlands, Australia, Japan, China, India, Singapore, Turkey, and the United Arab Emirates.

The primary data source was obtained for the following purposes, (1) Amazon was the world's largest B2C e-commerce platform [32], offering customers a wide range of products and a convenient shopping experience, and (2) the platform offered more benefits in terms of the quantity and quality of OCRs due to the extensive customer evaluation system [33]. Review from four electrical products were used for this study, namely Air fryer, Air purifier, Kettle, and Lamp. The product's name, rating, and text review were the information acquired during the data crawling from OCRs and subsequently stored in Ms. Excel document. Fig. 2 showed examples of Amazon OCRs.

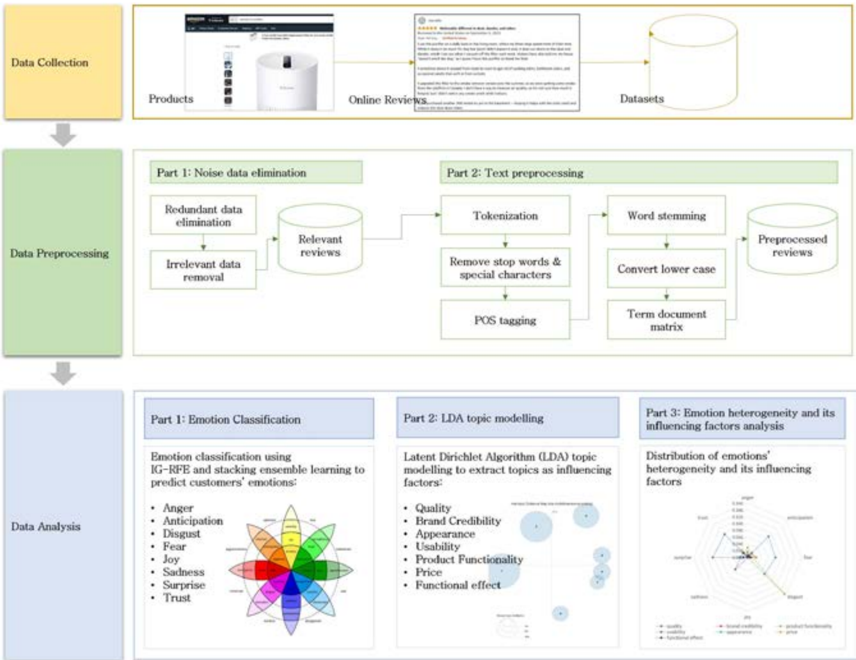
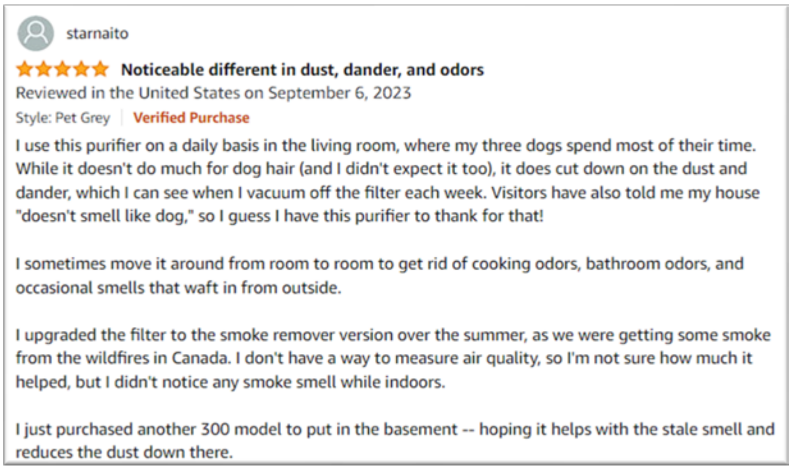


Fig. 1. Research Design Process

Previous studies showed that customers obtain information about products by reading internet reviews [34]. The content of OCRs fostered customer decision-making by facilitating informed decisions. These OCRs effectively lowered search costs by providing more information about products, services, and shopping experiences [35]. OCRs have a high probability of winning the trust of prospective customers and are more credible than information gathered through conventional surveys or interviews [36].


starnaito

★★★★★ **Noticeable different in dust, dander, and odors**

Reviewed in the United States on September 6, 2023

Style: Pet Grey | Verified Purchase

I use this purifier on a daily basis in the living room, where my three dogs spend most of their time. While it doesn't do much for dog hair (and I didn't expect it too), it does cut down on the dust and dander, which I can see when I vacuum off the filter each week. Visitors have also told me my house "doesn't smell like dog," so I guess I have this purifier to thank for that!

I sometimes move it around from room to room to get rid of cooking odors, bathroom odors, and occasional smells that waft in from outside.

I upgraded the filter to the smoke remover version over the summer, as we were getting some smoke from the wildfires in Canada. I don't have a way to measure air quality, so I'm not sure how much it helped, but I didn't notice any smoke smell while indoors.

I just purchased another 300 model to put in the basement -- hoping it helps with the stale smell and reduces the dust down there.

Fig. 2. Sample of OCR

2.3 Text Preprocessing

Textual data preprocessing typically comprised six phases including (1) Tokenization, dividing sentences into discrete phrases or tokens, (2) Cleaning, eliminating question marks, stop words, URLs, special characters, and numbers, (3) Part-Of-Speech (POS), each token to be marked up with words corresponding to specific parts of speech (e.g., adjective, verb, and noun), (4) Stemming, words were converted to the base term, (5) Lowercasing, all characters were converted to lowercase, and (6) Term-Document Matrix represented the frequency of each unique token (also called feature) within each document. This TDM served as the foundation for subsequent feature selection and emotion classification tasks.

2.4 Experiment 1. Emotional Heterogeneity Classification

Step 1. Data Labelling

The study aimed to identify feelings in textual data with the use of emotional analysis. NRC word-emotion association lexicon was adopted to show the hidden emotions of the customers [37]. The NRC Emotion Lexicon [38] was a lexicon that grouped words according to Plutchik's eight emotion dimensions [39]. The eight primary emotion dimensions including anger, anticipation, disgust, fear, happiness, sadness, surprise, and trust, were established by the psycho-evolutionary theory, and annotated into 14,182 English words. Plutchik [39] presented the concept of the eight basic emotions depicted in **Fig. 3**. Joy, surprise, anticipation, and trust were examples of positive emotions, while negative feelings included angry, anxiety, sadness, and disgust. The Plutchik's emotion model is selected in this study because Plutchik's model offers a comprehensive framework for comprehending the spectrum of human emotions. Also, Plutchik's model is considered as an adaptable instrument that may be used in a variety of contexts, for instance in psychology, counselling, and leadership as well as individuals who are looking to become more conscious of their emotions. It makes them easier to understand and to draw clear relationships between different emotions. **Table 1** describes the NRC Emotion Lexicon, the list of emotion dimensions, and the number of words associated with each feeling dimension.

Table 1. Words related to each emotion [38]

Emotion	Words
anger	bear, collusion, brute, casualty, clash, denounce, defense, disobey, disaster, detest
anticipation	arouse, charitable, confession, denying, eventuality, importance, opportunity
disgust	cancer, dabbling, coldness, creature, crude, dislike, dirty, disallowed, disappoint
fear	warning, tramp, tearful, teasing, suppression, supremacy, socialism, snake, slam
joy	blessed, charity, celebrated, cheerful, comfort, encourage, festival, hope, jump
sadness	alienated, anthrax, bad, bankruptcy, deterioration, cutting, dark, decay, depressed
surprise	bang, differently, blast, bomb, chance, bonus, curiosity, deal, death, detonate
trust	admirable, authoritative, brotherhood, comfort, pleased, commandant

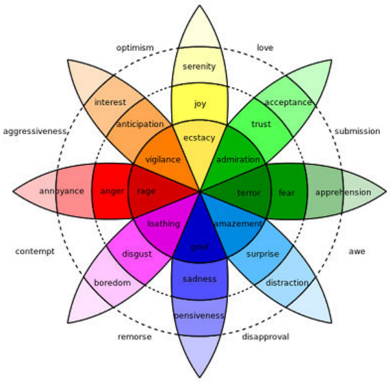


Fig. 3. Emotion Wheel [39]

Step 2. Data Balancing

Imbalanced datasets, where majority classes predominate and minorities were outnumbered [40], can lead to inaccurate predictions from learning models, particularly for the minority class. This was because the cost of false positives (incorrectly classifying a sample as belonging to the minority class) was often substantially lower than the cost of false negatives (not detecting the minority class). Oversampling techniques address this issue by increasing the number of samples in the minority class, promoting a more balanced distribution.

Step 3. Emotion Classification using Stacking Ensemble Learning.

The accuracy of classifier techniques was increased by carefully selecting the features. The feature referred to this study was the terms document matrix after data preprocessing. Each matrix had terms from the text review and their number of features was large and it caused high dimensionality problem. Therefore, feature selection was done to select only the most important and most relevant features.

There were two primary methods for feature selection namely (1) Wrapper methods based on classifier, and (2) Filter methods based on criteria [41]. The first stage, filter-based selection method serving as an Information Gain (IG) was used in the initial step to identify the key feature to assist this study in improved classification while applying the technique to datasets. A scoring system was applied to each feature during data separation and features with higher scores were considered more valuable.

The second stage, wrapper-based feature selection used in the study was the Recursive Feature Elimination (RFE). The weakest features were removed until the required number was eliminated [42]. The training model ranked the features by eliminating a certain number on each iteration. The aim was to remove any potential collinearity and dependencies from the model. The RFE eliminated noise, redundant, and irrelevant features through a sequential iterative step. The method created a new feature list based on the lowest weight criterion.

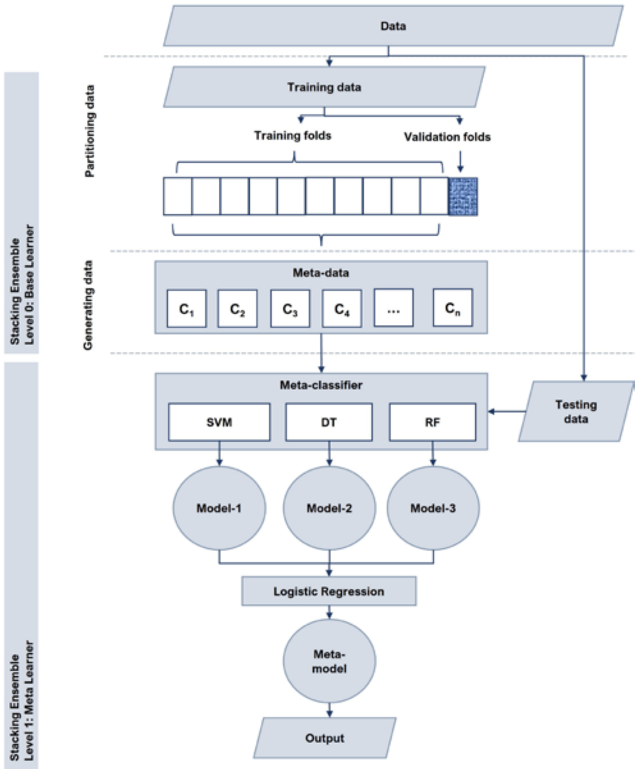


Fig. 4. Stacking Ensemble Learning Model for Emotion Classification

The eight emotion labels found in customer reviews were classified by using prominent machine learning models, such as (1) Support Vector Machine (SVM), (2) Random Forest (RF), and (3) Decision Tree (DT). The three classifiers were integrated into ensemble learning to improve outcomes. The fundamental principle behind ensemble learning was the fallibility and imperfection of machine learning models. The frameworks aimed to improve classification accuracy by combining the advantages of various base learners while reducing variance as well as bias errors related to individual machines. Boosting, bagging, and stacking were the three categories of ensemble learning methods [43-44]. However, the analysis focused on stacking ensemble learning to strengthen the model in this study.

Stacking was a two-stage procedure including the concurrent teaching base learners and feeding the outputs into a metamodel for combination based on [45-46]. To improve classification performance and generalizability stacking ensemble learning trained several base learners and combined the predictions. This method showed promise in improving model robustness and accuracy based on several studies [47-50]. The stacking ensemble learning model can be seen in **Fig. 4**.

Step 4. Emotion Classification Evaluation Metrics

A range of measures called performance metrics were adopted to assess the quality of the model. The performance of applied learning classifiers was further measured using accuracy as an assessment parameter. The accuracy was calculated by dividing the total number of correct predictions by the total prediction number.

2.5 Experiment 2. Topic Modelling

The study summarized the emotions hidden in text reviews to determine how the product's attributes were related to customers' emotions. Subsequently, the analysis introduced the Latent Dirichlet Allocation (LDA) topic model to extract attributes related to customers' emotions. Blei *et al.* [51] proposed the three-layer Bayesian probability model with a word-document-topic structure, known as the LDA topic model [52]. LDA can recognize potential topics in documents was represented by each subject with a probability distribution based on words. Furthermore, the hidden factors were extracted from the processed data using the LDA algorithm. The parameters K (number of topics) and the prior hyperparameters α (for the document-topic matrix θ) and β (for the word-topic matrix φ) were set because LDA is an unsupervised technique [53]. Changing the number K of subjects modifies the model's granularity, or degree of detail. The LDA topic model is shown in **Fig. 5**. The experiment results from this study consisted of predictive emotion classification and topic modeling for attribute extraction. This combined approach offered a deeper understanding of customer behavior by capturing both emotional responses and its influencing factors.

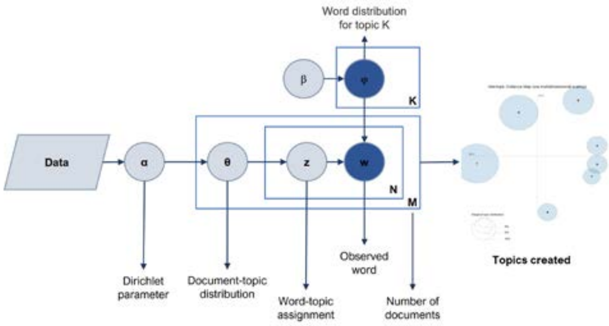


Fig. 5. Latent Dirichlet Allocation

3. Results

3.1 Experiment 1. Emotional Heterogeneity Classification Result

Fig. 6 showed the accuracy of the emotion classification results using a variety of machine learning models, including stacking ensemble learning, RF, DT, and LR. The stacking ensemble learning achieved maximum accuracy based on the outcome of the experiment. The performance was better than a single base classifier when several distinct learning algorithms were integrated into a single stacked ensemble learning method. Therefore, the outcome gained traction and was an efficient strategy in machine learning models. Numerous classification methods were assessed for the four datasets of Amazon OCRs that were shown in **Fig. 6**. The selected learning models were the foundation for the recommended ensemble model. **Fig. 6** showed that the proposed model had performed better when compared to existing models. Furthermore, **Fig. 7** showed a schematic representation of every classifier that had been applied to a particular dataset, indicating the proposed model at a maximum of 80.99% and the DT algorithm with the lowest accuracy of 68.57%.

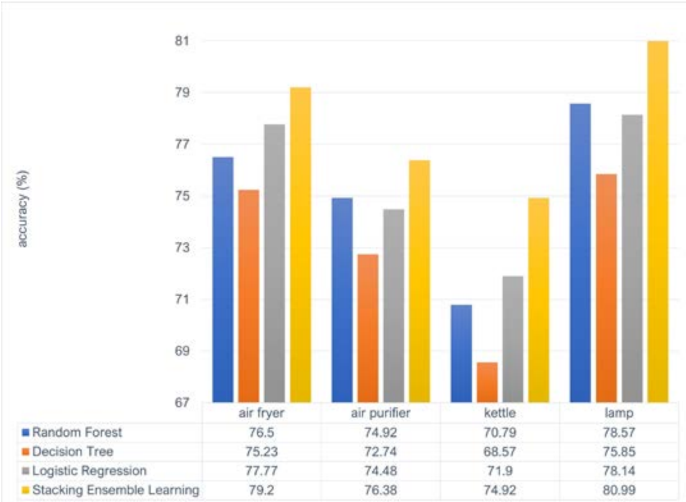


Fig. 6. Accuracy of Emotion Classification

The number of emotion labels identified in OCRs led to the inference that customer reviews towards the products was negative. Based on each product's emotion classification results, **Fig. 7** showed a bar chart of the emotional distribution. The chart indicated that there were more reviews with negative emotions characterized by anger, anticipation, fear, disgust, and sadness, than positive feelings such as joy, surprise, as well as trust. These negative reviews could be due to several factors such as product quality and customer service issues.

Following the identification of each review's emotion label, the study calculated the ratio of positive reviews to the number of total ratings to determine the customers' satisfaction level with each product. **Fig. 7** indicated the distribution of emotional tendency for each product with **Fig. 7** (a) further showcasing "joy" and "trust" for the Air fryer dataset and a smaller number of "anticipation" as well as "fear". This implied that even though the customer was satisfied with the product however there were still a few feelings of "fear" and "anticipation." **Fig. 7** (b) showed the radar chart of the Air purifier dataset. The emotions were diverse but mostly negative because the OCR had a substantial number of "disgusts", "fear", "anger", "anticipation", and "sadness" with the positive feeling only indicating "trust". The chart signified that the customers were not satisfied with the Air purifier. **Fig. 7** (c) showed the Kettle dataset which was dominated by negative feelings such as "sadness", "fear", "anticipation", and "anger". There was only a single positive feeling which was "joy." **Fig. 7** (d) had a composition of positive and negative feelings. The lamp dataset had positive feelings such as "trust" and "surprise" while negative emotions were "anger," "sadness", and "anticipation". The bar chart shown in **Fig. 7** only described the emotional tendency of each product in total. However, there was no detail information about which attributes of the product made customers disappointed. The next experiment would therefore extract attributes of each product using LDA topic modelling. This will enable analysis of which attributes required improvement based on the emotion extracted from OCRs on each attribute.

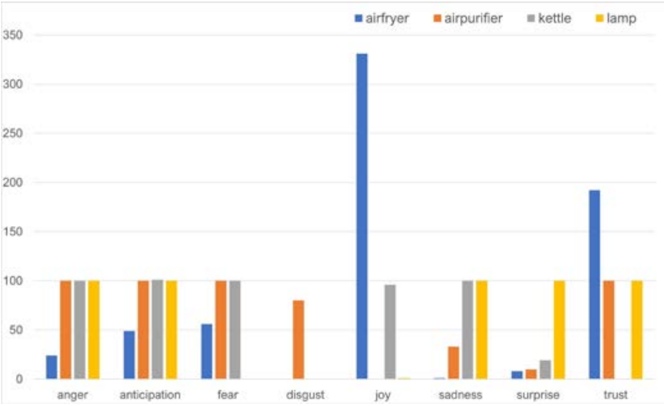


Fig. 7. Distribution of Emotional Tendency per Product

3.2 Experiment 2. Topic Modelling Results

Fig. 8 offered a visual representation of the LDA topic modelling result, allowing for the exploration of the key factor discovered in the data. On the left side, the related factors were represented by the numbers in the circles while the sizes and numbers of the circles corresponded to each factor. The top frequent words under each factor were observed to have the highest frequency on the right side of the chart.

In **Fig. 8**, the visualization of seven factors were shown as circles while the subjects were reflected in blue hue. Furthermore, the percentage of tokens included in the corpus was indicated by the size of the circle. The overlapping centres of these circles were determined by the estimated factors of distance [54]. Consequently, seven factors were identified from LDA topic modelling to determine the emotion and influencing factor for each product's review as shown in **Table 2**. Quality, brand credibility, product functioning, usability, appearance, price, and functional effect were the primary factors identified from the reviews.

Table 2. The Influencing Factors Extracted from OCR.

No.	Factor	Top words
1	Quality	filter, quality, change, apartment, living, great, perfect, different, good, time, easy, work
2	Brand Credibility	year, time, brand, review, reason, research, disappoint, negative, past, disclosure, aware, assure
3	Appearance	color, wide, range, great, brightness, beautiful, product, cover, appearance, corner, light, tone, dark
4	Usability	easy, use, work, time, great, clean, bedroom, nice, good, problem, living, modern
5	Product Functionality	range, work, remote, great, brightness, direction, wide, different, bright, room, light, good, ceiling, amazing, year, control, use
6	Price	affordable, great, light, discount, time, love, product, money, use, purchase, sale, order
7	Functional effect	product, work, good, unpleasant, water, review, help, quiet, filter, allergy, temperature, plastic, hot, smell

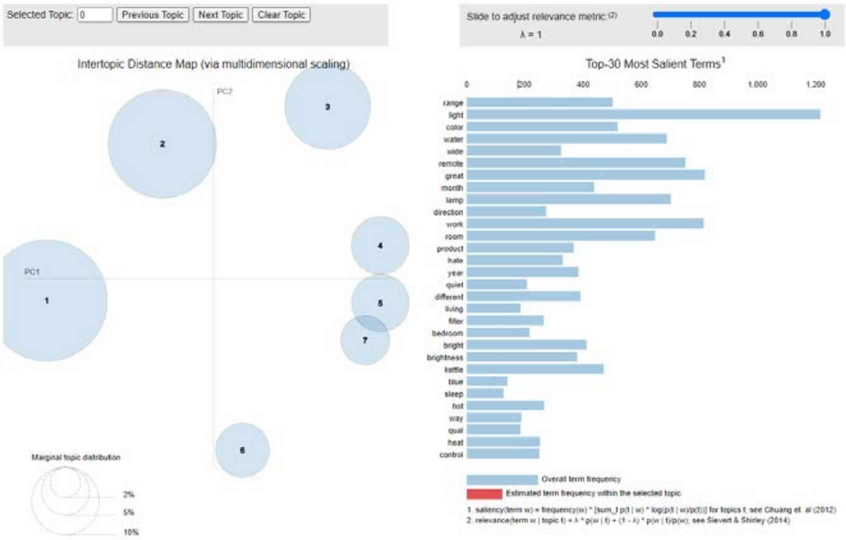


Fig. 8. The Visual Display of the Topic Modelling Result

3.3 Customer Emotional Heterogeneity Tendency and the Influencing Factor

The experiment aimed to verify the similarities and variations in the factors influencing emotional heterogeneity tendencies of customers for four distinct products. According to LDA topic modelling results in the second experiment, each review had been clustered and had an emotional tendency label from the first experiment. **Table 3** showed the proportion of OCR having factors representing each emotion. A difference in weight based on emotions and factors per product was observed and subsequently indicated in four radar plots, as seen in **Fig. 9**.

Table 3. Underlying Emotions in each Dataset

	Normalized							
Factor	Anger	Anticipation	Fear	Disgust	Joy	Sadness	Surprise	Trust
Air Fryer								
Quality	0.19	0.10	0.08	0	0	0	0.23	0.19
Brand Credibility	0.07	0.11	0.18	0	0	0.93	0.35	0.06
Product Functionality	0	0	0.02	0	0	0	0.22	0.03
Usability	0.23	0.35	0.25	0	0	0	0	1
Appearance	0.08	0	0.04	0	0	0	0	0.01
Price	0.27	0.20	0.12	0	0	0	0.12	0.21
Functional Effect	0.07	0.16	0.24	0	0	0	0	0.28
Air Purifier								
Quality	0.54	0.58	0.78	0	0	0	0.2	0.66
Brand Credibility	0.1	0.34	0.08	0	0	0.6	0.34	0
Product Functionality	0	0	0.04	0	0	0	0.2	0
Usability	0.76	0.6	0.68	0.8	0	1	0.6	0.78
Appearance	0	0	0.04	0	0	0	0.2	0
Price	0.18	0.24	0.14	0	0	0	0	0.02
Functional Effect	0.42	0.24	0.24	0.8	0	0.4	0.46	0.54
Kettle								
Quality	0	0.03	0.11	0.14	0	0	0.15	0

Brand Credibility	0	0.07	0.02	0	0	0	0.06	0.03
Product Functionality	0	0.09	0.02	0	0	0	0.07	0.01
Usability	0.03	0.22	0.19	0	0	0.43	0.06	0.23
Appearance	0	0.02	0.06	0	0	0	0.11	0
Price	1.00	0.50	0.59	0	0	0.56	0.60	0.56
Functional Effect	0.07	0.14	0.11	0	0	0	0.24	0.17
Lamp								
Quality	0	0.57	0.54	0.46	0	0	0.67	0.63
Brand Credibility	0	0.08	0.04	0	0	0	0	0.03
Product Functionality	0.19	0.12	0.09	1	0	0	0	0.09
Usability	0.06	0.11	0.16	0	0	0.33	0.14	0.13
Appearance	0.1	0.03	0.02	0	0	0	0.15	0
Price	0.06	0.08	0.17	0	0	0	0	0.13
Functional Effect	0.02	0.04	0.06	0	0	0	0.08	0.12

Fig. 9 (a) and **Fig. 9 (d)** showed in detail that the Air Fryer and the Lamp had a dominant emotional tendency while the other datasets indicated more diverse tendencies. The following were the emotional tendencies and influencing factors of each product.

(1) The Air Fryer dataset in **Fig. 9 (a)** had two major emotional tendencies which were "trust" from the usability factor and "sadness" from the brand credibility. Customers were satisfied with the usability of the product by showing "trust" emotion, despite feeling saddened due to the brand credibility simultaneously. Brand credibility itself is defined as the believability of the product position information contained in a brand [55]. Brand credibility comprised the consistent delivery of what was promised. Erdem and Swait [55] further asserted that the concept of credibility included trustworthiness as the main dimension, affecting customer choice and brand consideration more than expertise. However, attention should be given to the customers who felt sad about brand credibility. Despite exceeding trust in usability due to brand expectations, customer emotion from OCRs suggested a gap between expectations and reality.

(2) The Air Purifier dataset in **Fig. 9 (b)** indicated diverse emotions except "joy" feeling. These multiple emotions were mostly influenced by the "usability" and "appearance" compared to other factors. This confirmed that customers considered usability and appearance to be the most crucial factors of the Air Purifier product. According to previous study by Srinivasan *et al.* [56], an examination of customer behavior showed several factors contributing to customer loyalty to a product. Numerous factors were general appearance, customization, instructiveness, interface, and product line. Purani *et al.* [57] further added ease of use or usability of the product as a loyalty factor. **Table 4** showed pairwise comparison with the results indicating that there were significancy between usability and appearance on anticipation as well as fear emotions. It implied that two population data among appearance and usability factor had correlation with each other.

(3) The Kettle dataset in **Fig. 9 (c)** had neither "joy" nor "disgust" emotions on the OCRs. The emotion tendency of Kettle dataset was observed on variations. The emotions were dominated by "anger", and followed by "fear", "sadness" as well as "surprise", all influenced by the "price" factor. Customers were inclined to discuss price more often than other factors on this product, but the discussions were majorly based on negativity. In previous studies by Jo & Shin [58], price was often considered a key factor affecting customers' decisions, significantly regulating the relationship between each factor and purchase intention [59]. Additionally, Huang *et al.* [60] emphasized the importance of paying attention to the negative emotions of the public towards product prices. The results of topic modelling showed that customers were not only concerned about the price of

products, but also other factors as shown in **Fig. 9 (c)**. However, price was considered as a significance factor of the customer's positive emotions in Kettle dataset. Prior research by Xu and Duan [61], studied pricing strategies in e-commerce systems and explored the effect of customer disappointment aversion on the online seller's optimal decisions of pricing, ordering and quick response. Yao and Zhang [62] presented a model which contained an optimal combination of base and shipping price decision of internet retailers in a business-to customer (B2C) setting. However, the study further indicated that price, as a differentiated competitive advantages of products, could stimulate customers' positive emotions. **Fig. 9 (c)** evolved due to a noticeable focus, suggesting that many reviews complained about price in the Kettle datasets.

(4) The Lamp dataset in **Fig. 9 (d)** showed a "disgust" emotion from the "product functionality" factor, dominating OCRs. Furthermore, customers also discussed "quality" with diverse emotions. Customers felt "surprise", "trust", "anticipation", "fear", and "disgust" as observed in the chart. Quality as a key factor of customers' emotions was critical to improve the core competitive advantage of the product. Previous study by So *et al.* [63] found that the quality and price served as a "double-edged sword" affecting customers' emotional assessments of products. However, the analysis results were not in correlation to the findings of the previous study. Pairwise comparison pairing price and quality was performed with no significance discovered as seen in **Table 4**. This implied that the study disagreed with the concept of a "double-edged sword" between quality and price. According to Srivastava *et al.* [64], product quality metrics were defined as a dynamic condition reflecting the ability to meet customer needs and expectations, thereby being beneficial to the user. Customer perceptions of product quality vary, reflecting individual priorities and needs. A strong awareness and confidence in the advertised performance of trusted brands were more inclined to be observed by customers who care about product quality [65].

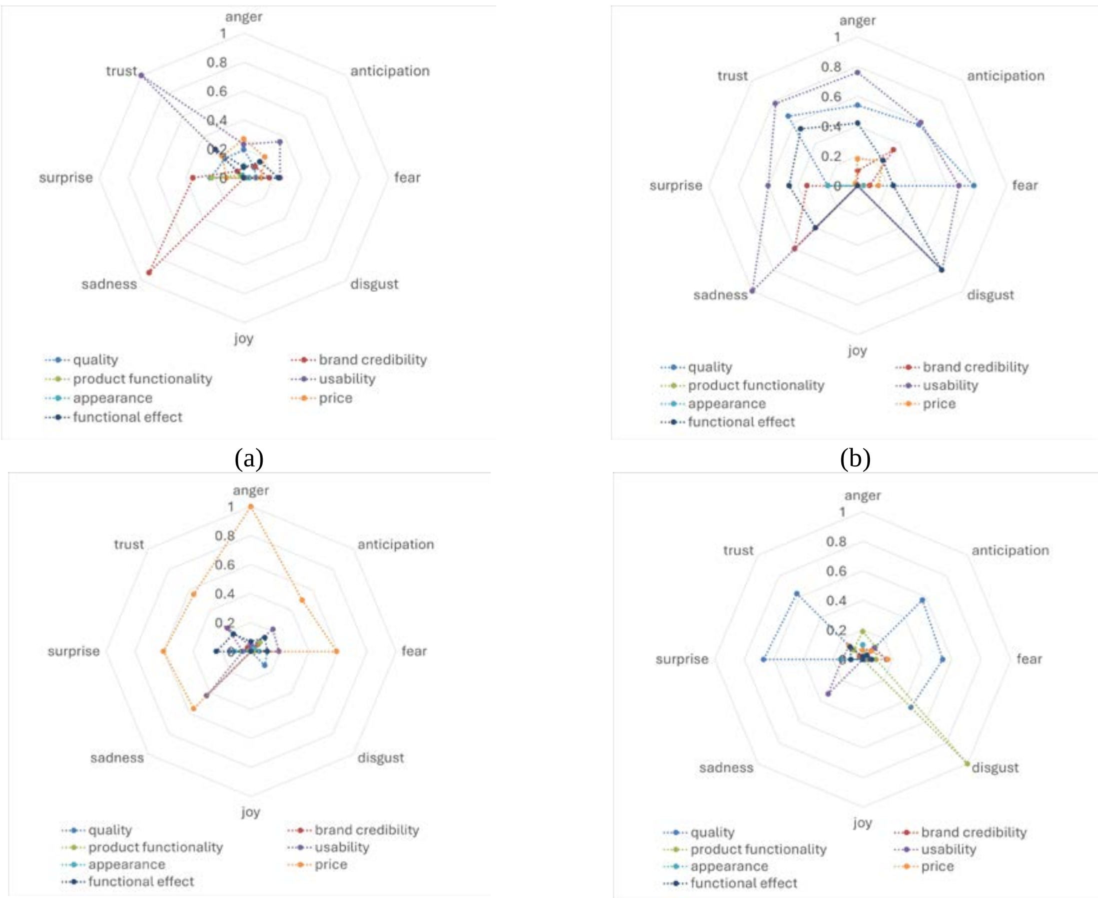
Table 4. Pairwise Comparisons (*p-value*)

Paired Factors	Anger	Anticipation	Fear	Disgust	Joy	Sadness	Surprise	Trust
Quality-Brand Credibility	0.20	0.32	0.22	0.27	-	0.26	0.50	0.15
Quality-Product Functionality	0.53	0.16	0.08	0.52	-	-	0.32	0.15
Quality-Usability	***0.04**	0.97	0.73	0.81	-	0.06	0.35	0.61
Quality-Appearance	0.43	0.13	0.12	0.27	-	-	0.19	0.11
Quality-Price	0.43	0.86	0.77	0.27	-	0.39	0.61	0.75
Quality-Functional Effect	0.56	0.40	0.38	0.81	-	0.39	0.41	0.63
Brand Credibility-Product Functionality	0.82	0.34	0.51	0.39	-	0.26	0.24	1
Brand Credibility-Usability	0.11	0.06	***0.04**	0.39	-	0.94	0.83	0.13
Brand Credibility-Appearance	0.66	0.053	0.37	-	-	0.26	0.62	0.09
Brand Credibility-Price	0.22	0.34	0.30	-	-	0.56	0.93	0.15
Brand Credibility-Functional Effect	0.19	0.87	***0.02**	0.39	-	0.33	0.88	***0.02**
Product Functionality-Usability	0.32	0.11	***0.03**	0.64	-	0.06	0.83	0.15
Product Functionality-Appearance	1	0.19	0.83	0.39	-	-	0.88	0.23
Product Functionality-Price	0.28	0.14	0.17	0.39	-	0.39	0.66	0.18
Product Functionality-Functional Effect	0.60	0.33	0.17	0.76	-	0.39	0.76	0.054
Usability-Appearance	0.24	***0.03**	***0.02**	0.39	-	0.06	0.57	0.12
Usability-Price	0.58	0.78	0.93	0.39	-	0.29	0.81	0.41
Usability-Functional Effect	0.17	***0.03**	0.10	-	-	0.06	0.89	0.27
Appearance-Price	0.26	0.08	0.14	-	-	0.59	0.12	0.12
Appearance-Functional Effect	0.52	0.058	0.08	0.39	-	0.39	0.43	***0.016**
Price-Functional Effect	0.33	0.25	0.52	0.39	-	0.65	0.79	0.97

Note. * Significant at *p-value* < 0.05

Pairwise comparisons using t-tests was performed to determine the differences between pairs as shown in **Table 4**. Multiple t-test between all combinations of pairs was computed to calculate the pairwise t-test. The number of *p-value* in **Table 4** shows the significance between pairs. If *p-value* less than 0.05 then there is a significant difference between the compared groups. The results of pairwise t-test comparison were determined as follows.

(1) The quality factor indicated an increased use of words representing “anger” in relation to usability.
(2) The brand credibility showed an enhanced use of words reflecting “fear” and “trust” in relation to functional effect.
(3) The brand credibility showed an enhanced use of words reflecting “fear” in relation to usability.
(4) The product functionality indicated an improved use of words constituting “fear” in relation to usability.
(5) The usability showed an increased use of words representing “anticipation” and “fear” according to appearance.
(6) The usability reflected an improved use of words indicating “anticipation” in relation to functional effect.
(7) The appearance showed an increased use of words representing “trust” according to functional effect.



(a) (b)

(c) (d)

Fig. 9. Distribution of Emotion Tendencies Per Product of Each Factor (a) Air Fryer (b) Air Purifier (c) Kettle (d) Lamp.

4. Discussion and Implications

4.1 Discussion

OCRs by customers on e-commerce platforms could influence other feelings and general assessments of the product. Consequently, the analysis develops an integrated predictive emotion classification and topic modelling from OCRs. The study focuses on the product's attributes most valued by customers and the correlation with customers' emotions. The findings show that seven attributes are identified as influencing factors in the OCRs of the four sampled products including quality, brand credibility, product functionality, usability, appearance, price, and functional effect. There are significant differences in the frequency of these emotions related to the attributes, reflecting customers' emotion between distinct factors [23].

The study discovered that the value customers place on attribute depends on the type of product. Additionally, the emotion classification results show that customers are dissatisfied with the products having large number of negative reviews. Most customers' perceptions of the product with substantial number of negative reviews are unfavourable and include feelings of sadness, disgust, anger, anticipation, fear, and surprise. Multiple product's attributes influence customers' emotions and satisfactions, signifying that customer perceptions and evaluations of these factors have negative predictive effects. This is based on the extraction of hidden emotions from customer review text related to each factor. The study clarified that customers' opinions of a product are influenced by the perceptions and assessments of its style, price, functional impact, brand credibility, and usefulness.

According to Srivastava *et al.* [64], purchase decision is a customer's preference to either acquire a particular product or not. Among the several factors influencing the purchasing decision, customers often consider products that are well-known to the public for its quality and price. Customer typically progress through several stages based on the five key purchasing decision indicators before obtaining a product [66]. These phases includes (1) interest and need recognition, identifying a product needs or desire for a particular products, (2) information search, obtaining information about personal and family needs related to the product, (3) alternative evaluation, comparing different products, brands, and prices, (4) purchasing decision, selecting between simple options or favoring established brands, and (5) post-purchase behavior, evaluating satisfaction and potentially recommending the products to others.

Although previous study has focused on extracting several attributes from textual OCR, the intrinsic relationship has not been considered [67-68]. The relationship generates high comprehensible textual labels for identifying and classifying emotion according to product's attributes. This adds to the theoretical base for comprehending the behavior of customer reviews. This study expands the area of research on customers' emotional tendency by indicating the influencing factors of different emotions from the heterogeneity aspect. Previous study examined the causes and effects of the factors of customers' positive emotions, such as pleasure and attachment [63][69]. However, the results only showcased pleasant emotions and did not thoroughly examine the antecedents of the various feelings that customers experience. This study applies multiple techniques to extract the different emotional tendency from customer reviews and investigates further into the factors influencing customers' emotions. Zhu *et al.* [70] also extended the boundaries of ratings study by focusing on distinct emotional information hidden in OCR texts. The study provided multiple heterogeneity perspectives in place of a single viewpoint when analyzing customers' emotional tendency. The results strengthen the discrepancy between the theoretical study and the emotional variety of customers in practice by adding to the antecedent components of the varied emotions. By delving into the reasons behind customer emotions in reviews, the study clarifies both demand characteristics and emotional experiences. Additionally, the analysis offers perceptions into the consuming tendencies and rationale for customer behavior in the business model.

The valence of OCRs has previously been studied using a dichotomy (positive vs. negative) or trichotomy (positive vs. neutral vs. negative). Using Plutchik's eight emotion dimensions, the study investigates more in-depth emotional dimensions. The results offer a clearer explanation for customer's review behavior as well as an accurate picture of the thoughts and experiences. Despite the difficulty in having a thorough understanding of the various emotional causes behind customers' complexes, there have been few systematic studies that explicitly address these challenges. Therefore, the study uses customer reviews from the Amazon platform, and the reasons are extracted from the feedback using a combination of methodologies.

The study completes the theoretical framework for studies on the reasons for customer emotional heterogeneity in products by elucidating the various emotional influencing factors, alongside the similarities and differences. Previous study has focused more on the emotional tendency or authenticity assessment of customers. For instance, Luo & Tang [71], and Zhu *et al.* [70] evaluated experience and service quality according to emotional tendency, while Cheng & Jin [72], and Liu *et al.* [73] investigated the relationship between review attribute characteristic and customer emotion. However, the studies limit the ability to fully understand the causal logic underlying the emotional heterogeneity of customers. The limitation occurs due to the focus on the classifications of customers' emotions rather than delving deeper into the underlying causes. Consequently, this study examines the similarities and differences between the customers and obtains various emotions based on an evaluation of emotional tendency. Building on the work on customer emotion evaluation, comparison was performed on the emotional causes of different tendencies in this study. The findings provide a comprehensive theoretical explanation for the causes and internal logic of customer emotional heterogeneity, strengthening the study's foundation on the causes of customers' emotions.

Two-stage feature selection was integrated by the study to reduce computational cost of modeling and applied stacking ensemble learning emotion classification to improve the performance of a predictive model. Additionally, it thoroughly obtains various emotional information from customer reviews using LDA and machine learning models. The analysis further provides a new technological application concept for customer emotional study on Amazon platform. Previous study has mostly used questionnaires and in-depth interviews to examine the emotional components of the customer experience [61][69].

4.2 Implications

This study offers various practical implications as contributions to the body of knowledge. Initially, the proposed model helps academics and practitioners find customer review trends quickly and creates tools allowing users to explore, understand, and evaluate feedback from different angles more effectively. The study subsequently offers an innovative method for summarizing customer review material, and the proposed model creates attribute ratings combined from every feedback to develop a concise summary. A business can precisely understand customers' needs and wants through the examination of textual content on each of the primary attributes.

The proposed model allows for the ranking of product listings to be customized. Most review websites offer little or no ranking alternatives for customers' searches. For instance, there is no product listing ranking offered by Amazon. Yelp sorts the listings with three options namely best match with filter, highest rated, and most reviewed, while TripAdvisor ranks the listing with four options including traveler ranked, best value, lowest price, and distance. No other websites provide rankings or filter the listings/products according to a particular attribute. There are few websites that request reviews to rate pre-defined attributes with star rating as pointed out by the literature. Consequently, using pre-defined attributes to rank or filter products remains difficult. OCR platforms should use the proposed model to rank and extract attribute dimensions from plain-text reviews. Amazon should compile the results of the attribute and emotion ratings while offering recommendations to customers based on the findings.

The eight emotion dimensions' distributions for the seven factors also provide strategies for industry practitioners. Using the proposed model, the precise emotional tendency toward a particular product's attributes will be established rather than just general positive or negative emotion. Manufacturers can quickly determine when customers are happy, unsatisfied, losing trust, or upset with the specific attribute of the product [38]. By analyzing emotional tendencies, customers can create an "emotion-awareness system" to identify the causes of product and service failures and take appropriate action.

5. Conclusion, Limitations, and Future Research

In conclusion, this study offered an alternative viewpoint for analyzing customers' emotions and provided insights on which attributes customers value most by conducting a predictive emotion classification and topic modeling of various OCRs of product on Amazon. This study contributed to the field by exploring an original concept that has not been investigated before by integrating of emotion classification and topic modelling. This study extracted eight emotions from the OCRs that were anger, anticipation, disgust, fear, happiness, sadness, surprise, and trust. Using LDA topic modeling, the findings showed that a variety of product attributes were taken into consideration when evaluating a product by customers, including quality, brand credibility, product functioning, usability, appearance, pricing, and functional effect. As an overall evaluation, eight emotions related to each attribute per product were identified. The results assisted scholars and manufacturers in better understanding the primary emotions that customers experience when purchasing a product, which would be beneficial in both innovation and marketing.

The study was without limitations despite the adoption of a new perspective. Customers' emotions toward the four products were the only feelings investigated. Despite the efforts to include a wide range of representative products and attributes in the study, it remained impossible to cover all products and attributes. Additionally, the study prioritized the independent effects of product attributes over the interactions. Future studies based on the results about the statistical interaction between attributes could produce some insightful conclusions.

The major data used in this study originated from the OCR on Amazon which were from a single website, potentially introducing bias. Uncertain applicability to social media platforms limited the generalizability of the findings. Therefore, future studies should gather OCR from multiple websites for the same e-commerce platforms.

The study merged big data and social network analysis to offer theoretical insights and practical implications for identifying the emotional heterogeneity of customers and the influencing factors. However, several limitations such as cultural differences were often neglected in research. There were variations in the development and operation models of platforms across various cultural contexts. Therefore, the results of this study may potentially complement the emotional heterogeneity and causes of customers in various cultures for future studies.

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